Tobacco-Free Policy Reduces Combustible Tobacco Byproduct on a Large University Campus

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We thank the University of Kansas Tobacco-Free Campus Steering Committee and Provost's Office, especially Heidi Garcia and Ola Faucher.

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Compliance with Ethical Standards

Data availability

The datasets generated and analyzed during the current study are available in the Open Science Framework repository, REDACTED.

Conflicts of interest/Competing interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Consent to participate

Not applicable.

Ethics approval

Not applicable.

Code availability

Not applicable.

Funding

Kansas Health Foundation Grant

Abstract

Recent years reflect an increase in public-campus adoption of tobacco-free regulation. Lower planning and implementation costs make campus-level policy a convenient proxy for broader public policy. Given the implications for community-level behavior change, demonstrating policy-level effects via behavior analytic planning is of value. The present study examines combustible tobacco-product refuse accumulation on a large university campus preceding and following the enactment of a tobacco-free policy. We compared waste across four sites flagged by preliminary surveying among campus faculty, staff, and students. Widely interpretable statistical testing suited for simple time-series research designs supplements visual analysis. Results suggest (a) a meaningful and sustained reduction of tobacco byproducts in all locations and (b) a demonstrative extension of behavior analytic evaluation to a policy with plausible community benefit.

Keywords: *tobacco, cigarette, public policy, statistic analysis, behavior analysis*

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Effective public policy is critical to influencing behavior at scale, particularly in combatting community health disparity. Ongoing legislative campaigns target cigarette and nicotine dependence as a crucial public health venture. In the push for tobacco-use regulation, many public campuses (e.g., universities, hospitals) have adopted “tobacco-free” policies prohibiting on-site possession or use of tobacco-containing combustible and smokeless products (see Glassman et al., 2011; see also Wong et al., 2020). As of July 2020, at least 2,511 U.S. and Tribal universities had declared smoke-free and/or tobacco-free policies, 2,076 (83%) of which had placed additional bans on non-combustible product substitutes (American Nonsmokers’ Rights Foundations, 2022; see also Wang et al., 2018). These campus-scale implementations offer a demonstration of policy-contingent effects retained within clear boundaries of contact (i.e., solely campus employees/visitors); that there is an apparent parallel with broader community enactment infers scalability. As such, campus-level tobacco regulation provides a unique opportunity to probe the value of behavior analytic planning and input for policy design (and the applicability of behavior analytic methodology for public health therein; see Normand et al., 2021).

Tobacco-free campus policy has drawn substantial interest from outside behavior analysis (see Bardus et al., 2020). To date, an interdisciplinary body of literature targets policy compliance and outcomes such as barriers/facilitation of policy implementation (e.g., Hellesen et al., 2021; Lee et al., 2015), general audience reception (e.g., Braverman et al., 2021; Bommelé et al., 2020; Mamudu et al., 2012; Pignataro & Daramola, 2020), attitudes toward smoking and other substance-use as a function of policy enactment (e.g., Butler et al., 2011; Fitzpatrick et al., 2009), and methods for measuring population compliance with campus policy (e.g., Fallin et al., 2014; Russette et al., 2014), with these latter efforts heavily employing self-report measures (e.g., Allen & Stuart, 2019; Chuang & Huang, 2012; Cruz et al., 2015). Despite this literature, relatively few studies examine markers of demonstrable change in behavior following local policy enactment. Demonstrating such changes improves understanding of the effects of policies as applied (i.e., within said unique context) and the sensitivity of research tools to community-level changes in behavior.

Only a small sample of the reports documenting tobacco policy compliance describes efforts to observe smoker behavior directly. Fitzpatrick et al. (2009) examined smoking rates in designated outdoor shelters after implementing an indoor tobacco-use ban on a hospital campus. Harris et al. (2010) studied smoker behavior under a policy banning combustible tobacco use within 25 feet (7.62 m) of university campus buildings. Gatto et al. (2019; see also Burke et al., 2015) paired direct observation with geographic information system (commonly "GIS") mapping to assess overall compliance with enacted tobacco-free policies. Together, these studies provide preliminary support for applying straightforward data collection methods to campus-level policy evaluation. Yet a leading challenge in direct observation of cigarette smoking, such as that described here, is the degree to which resources (e.g., planning, person-hours, input from the smoking community) are required to accurately record smoking as it occurs. A mismatch of location or timing during planned sessions may misrepresent policy effects. As an alternative approach to direct campus tobacco-use observation, attention to behavioral byproducts[1] offers the advantage of a permanent product that (a) remains stable after discard and (b) is easily tracked over sessions (e.g., Clemons et al., 2018; McIntosh et al., 2016; Seitz et al., 2011).

[1] Reduction of cigarette litter embodies a socially valid outcome and a hallmark effect of historically successful tobacco-free policy adoption (e.g., Bresnahan et al., 2015).

Precedence stands in field literature for using permanent product recording to inform policy design. Geller et al. (1980) demonstrated the value of waste-receptacle salience for improving proper disposal practices by consumers in an indoor shopping mall. Across two experiments, supplemental data collection took the form of direct counts of waste *not* deposited in the modified receptacles. Count of mall litter and examination of ashtray contents together produced data supporting the use of modified receptacles to change visitor behavior. Similarly, an accruing body of research uses outcome measures to evaluate the efficacy of policy-relevant interventions to promote appropriate waste handling (e.g., Austin et al., 1993; Brothers et al., 1994; Szczucinski et al., 2020). O'Connor et al. (2010) demonstrated an increase in properly recycled plastic bottles on a college campus following a change in the salience, count, and placement of receptacles. The primary dependent variable was a daily count of plastic bottles placed in respective trash and recycle bins. Further work along a similar vein would continue to validate widely applicable methods for collecting data pertinent to policy-level behavior change mechanism evaluation.

From an analytic perspective, measuring and validating policy outcomes also presents methodological hurdles that may undermine the use of model time-series designs (see Biglan et al., 2000; Fawcett, 1991; see also Sherman & Sheldon, 1991). For instance, reversal designs would logically require withdrawing a policy effect over an extended duration of monitoring. Given the reasonable expectation of favorable health outcomes for target communities and the potential that policies were democratically chosen for enactment by (and are thusly presumed to be contacted by) those communities, such a policy withdrawal might be considered ethically dubious and could undermine public trust in policymakers. Regulation takes time and input from many invested parties, so issues of cost complicate using multiple-baseline approaches.

Moreover, considering that the homogeneity of samples is often unknown in multiple-baseline designs across people or groups—especially for large-scale evaluations—additional uncontrollable factors likely abound. Thus, the use of many prototypical single-subject time-series designs may introduce prohibitive complications that diminish confidence in the generality of the findings and lack social validity when analyzing public policy effects at scale. A likely result for any such policy analysis attempt is a simple experimental arrangement that often lacks the hallmark time-staggered analysis of field methods (e.g., Agras et al., 1980; Schroeder et al., 2004; Seaver & Patterson, 1976; Wilde, 1991).

Despite the aforementioned concerns with single-case design evaluations of policy, communicable findings on the magnitude of behavior change resulting from prospective regulation should not be beyond the domain of behavior analysis. Data-driven policy development (both organizational/institutional and political) and evaluation is an underrepresented but ripe area for field study (e.g., Watson-Thompson et al., 2013; Stewart et al., 2021; see Bonner & Biglan, 2021; Todorov & Lemos, 2020; see also Baer et al., 1987; Biglan et al., 2020; Bonner et al., 2021). Indeed, field literature already explores some broader-scale behavior change mechanisms. For instance, Van Houten and Nau (1981) examined the extent to which public posting—a low-cost implementation with real policy implications—influences rates of speeding on a public highway. Researchers placed highly discriminable signage at the threshold of a reduced speed region to provide feedback on weekly population speed limit compliance. Morning and evening sampling suggested a significant ability of signage to reduce rates of speeding. Combined with preceding planning efforts, field capture of policy-relevant effects signals potential to contribute to empirical legislation, from conception to assessment (see Fawcett, 1988).

Supplemental analytic approaches may be helpful to increase confidence in findings by audiences more accustomed to statistical interpretations (e.g., Seekins et al., 1988; Stokes & Fawcett, 1977); that is, translating to the more widely spoken language of probability and effect size (see Craig & Fisher, 2019). For this reason, there is a recent push for behavior analysts to adopt statistical methods to complement visual displays/inspection (see Young, 2018). Results of statistical analyses are typically required by granting agencies, support credibility across multiple fields, and are much more likely to be included in subsequent meta-analyses (Huitema, 2011). Although less commonly observed in the literature, linear regression can be performed in ways that complement traditional visual analysis components, providing objective descriptions of times-series design elements. Huitema (2011) lists four approaches for modeling effects in times-series designs. Generally, these four options consist of two methods for evaluating changes in the *level* of the dependent across phases or changes in both the *level* and *slope* across phases. In the interest of demonstration purposes, this use of established and familiar (i.e., requiring knowledge of statistical approaches typical of social scientific laboratories and policy advocates) supplemental analyses is a worthwhile preliminary focus. Of all areas of application and dissemination within behavior analysis, policy development may benefit the most from supplementary statistical data, given the multidisciplinary nature of the audience and the need for succinct and actionable data descriptions to potentially effect change for large swaths of the population.

Campus-level tobacco policy is a convenient proxy for broader policy. A closer examination of the relation between these product bans and resulting refuse—between change levers and behavior—should prove both fruitful and impactful. The purpose of the present study is to provide a preliminary report on the rate of cigarette butt litter found on a large university campus preceding and following the enactment of a tobacco-free policy. We hand-counted cigarette butts found in student-reported high-traffic smoking locations across multiple semesters. Visual analysis and supplemental statistical analysis using regression offer evaluation of changes in the level and slope of cigarette butt litter following policy enactment.

Method

Tobacco-Free Policy Development

The policy discussed here resulted from over five years of planning by a large Midwest university. Policy development began in 2013 with social validity surveys of the student body and faculty/staff; these results suggested a positive opinion on creating a more restrictive on-campus smoking policy. A policy steering committee was assembled in late 2013 that included student representatives, county health department personnel, human resources staff, behavioral science faculty, and students. As part of the initial policy development, the steering committee successfully applied for and was funded by a grant from the Kansas Health Foundation to support campus activities and to obtain consultation from the National Center for Tobacco Policy. Over several years, the steering committee worked to obtain support from various campus entities and personnel groups, develop empirically informed policy language and health messaging tactics, and policy implementation benchmarks, standards, and data monitoring efforts. The policy went into effect July 1, 2018, and prohibited smoking and tobacco use on the campus, with some limited exclusions. A portion of the policy also guaranteed campus constituents with tobacco cessation resources and supports (see the full policy at REDACTED).

As the "behavioral scientists" informing the policy, we carefully considered the behavior analytic literature in making recommendations. We relied extensively on Fawcett and colleagues' (1988) roadmap to using behavior analysis in public policy efforts, as well as Stolz's

(1981) “critical variables” in fostering policymakers’ adoption of behaviorally informed innovations. First, we held numerous “town hall” style meetings with campus stakeholders and groups to explain the planned policy and better understand the social validity of our goals and methods (Wolf, 1977), and ascertain the outcome variables they would describe as successful. Second, we relied on individualized marketing based on the social validity surveys (e.g., using a “respect others” messaging approach rather than “smoking is bad”). Third, we used Hursh and Roma’s behavioral economic approach to public policy (2013); that is, we increased effort for tobacco use—but did not require cessation—by permitting campus patrons to be exempt from the policy when in their private vehicles, regardless of campus location, while also decreasing effort related to accessing cessation treatments and products (i.e., potential behavioral economic substitutes). Fourth, we created a feedback mechanism with the Human Resources department so that campus patrons could report areas of policy infringement and/or personnel/staff who violate the policy. Fifth, we used an empirical approach to identify sites for policy signage and direct observation (see next section).

Site Identification

As part of the policy-implementation planning effort, we conducted a campus-wide survey of all university faculty, staff, and students approximately 8 months before the tobacco-free campus policy launch. A key focus of the survey was to provide respondents an opportunity to indicate on a map where they most typically observed smoking behavior (cf. the scatter plot approach proposed by Touchette et al., 1985). Upon approval by the university human subjects review committee (REDACTED), we sent the survey via the university’s Provost’s office. We obtained results from 3,422 respondents (2,216 students; 1,206 faculty/staff), with a median age of 23 years (*M* = 30.51; *SD* = 14.39). Of this sample, 2,987 respondents reported never smoking.

Using the Qualtrics (https://www.qualtrics.com/) Heat Map question type, we budgeted respondents with 3 clicks to make on a map of the university main campus, with an instruction to "Think about where you see the most amount of smoking on campus. Click up to three areas where you typically see the most amount of smoking."

Figure 1 shows the aggregate heat map based on respondent clicks. Denser areas of click aggregation create "hotter" spots, depicted by dark-colored shaded regions. That so many respondents identified four distinct clusters of smoking spots on campus conveys a substantial degree of confidence in the self-report methods. Given the robust finding of four primary smoking areas, we selected those locations for observation (described below).

Location A

Location A is a stretch of sidewalk, stairs, and benches near a busy transit hub and is centrally located with respect to campus layout. Several active campus buildings bordered the region. The observed segment measured approximately 1196 m^2 and contained, before policy enactment, two cigarette ashtrays.

Location B

Location B is a stretch of sidewalk and picnic tables directly adjacent to the campus student union, a location frequented by students, faculty, and staff (including drivers for the city transit company). The observed region comprised approximately 1087 m^2 and contained 6 public picnic tables. Before policy enactment, the location included two cigarette ashtrays.

Location C

Location C is a large common area (approximately 4579 m^2) shared by several first-year dormitories and mixed facilities; the boundaries of Location C subsumed a mid-size dining facility staffed by an off-campus affiliate company, as well as five cigarette ashtrays before policy enactment. The site does not border any academic building but is considered an active location based on the volume of residence halls within proximity. Students and staff regularly frequent Location C.

Location D

Location D is a relatively smaller grassy region bordering a large, active academic building. The observed segment measured approximately 63 m^2 and contained one cigarette ashtray before policy enactment.

Data Collection

We gathered data in conjunction with campus facilities to suspend mowing and other potentially disturbing landscape activities during butt counting and removal periods. Baseline data collection began approximately 10 weeks before policy implementation (see specific dates across the x-axis in Figure 2). Data collection occurred across four collection periods of three weekly sessions comprising eighteen total months of counting. Before each data collection period, counters cleared locations of all existing refuse to facilitate the calculation of weekly accretion. Counters then re-visited each location at a consistent weekly time (allowing one whole week to elapse between extraction) to collect refuse, yielding a per-week rate of byproduct accumulation.

The first two authors initially collected and counted all data. Counters began in a regular, pre-decided corner of the allocated zone and gradually swept the region to the opposite corner in an intentional and planned manner. The counters collected ashtray refuse data before the policy-coinciding language dictated ashtray removal. In cases of natural debris (e.g., leaves) accumulations obstructing the view of refuse, counters rearranged debris to search for underlying butts. Counters included atypical objects appearing as a byproduct of tobacco-product combustion (e.g., standard- and tipped-cigars); counts did not include fragments showing apparent signs of degradation (e.g., only a cotton filter). Counters counted and bagged butts on site, and an outside aid then re-counted those butts for reliability at a later date.

Count Reliability

To assess reliability, an independent observer re-counted the bagged butts for three sessions comprising eight (73%) weekly observations. We calculated reliability by comparing sum counts of all butts collected during each composite semester session (i.e., several weeks' observations); final values were the proportion of agreements to the sum of agreements and disagreements. Observer agreement was 99.5%, 97.7%, and 99.0% for Spring 2018, Fall 2018, and Spring 2019, respectively.

Statistical Analysis

We performed linear and generalized linear regressions to quantitatively assess the effects of policy enactment on the rates of litter observed across several sites. Specifically, we performed and compared two forms of GLS regression to identify which modeling strategy best characterized the observed data. The approach for quantifying effects in single-case designs reviewed in Huitema (2011) allows for an exploration of how the introduction of some independent variable influences response rates. Specifically, Model III quantifies baseline level and slope to generate separate predictors that index the observed *changes* in level and slope, respectively. That is, the approach provides a quantitative complement to the traditional behavior analytic practice of inspecting visual data to detect a clear and noticeable change in level (i.e., immediately following a phase change) or a meaningful change in slope (e.g., a downward trend in baseline changes to an upward trend in intervention). Similarly, Model IV achieves the same purposes but is limited to changes in level and is generally the more parsimonious model when minimal trending occurs in the data. Regardless of the use of Model III or Model IV, each provides a supplement to the traditional interpretation of single-case evaluation in the context of group-design methodology, thus yielding output effective for communicating findings to those historically versed in statistical analysis. Models I and II examine the same factors using Ordinary Least Squares (OLS), respectively, but are limited to cases where linear assumptions are met (i.e., absence of autocorrelation).

Models I/III featured a 4-item design matrix that quantified baseline levels (1), baseline slope (2), changes in level from baseline (3), and changes in slope from baseline (4). Alternatively, Models II/IV featured a 2-item design matrix that quantified baseline levels (1) and changes in level from baseline (2). For Model III/IV, the regression was performed using Maximum Likelihood Estimation and modeled a lag-1 autocorrelation structure for Time, nested within each Location. Each approach was robust to potentially relevant levels of autocorrelation in the modeled residuals. Model IV was considered a nested form of Model III, permitting systematic comparison using traditional model selection methods. We compared the fits for each model using Likelihood Ratio Tests (LRTs), wherein the null hypothesis was that the simpler was a more parsimonious approach to characterizing the data. A Durbin Watson test was performed on the OLS version of the optimal model to confirm the expected presence of significant autocorrelation.

Results

REDACTED documents all data and analytic output for the work described above. At each site, we made 11 sweeps comprising four observation periods; collection did not occur during the third week of Fall 2018 (11/9/2018) due to cold temperatures, high wind speeds, and precipitation. Figure 2 displays raw cigarette butt counts for Locations A-D and associated statistical predictions. Note that the locations feature substantially differing y-axis scales, indicative of the variability in cigarette butts collected during baseline. Baseline levels of cigarette butts collected were relatively stable within each location. Locations A and D featured a relative decrease in the third week of the baseline data collection, compromising confidence in the visual inspection of effects and necessitating a large effect to infer any functional relation. It is worth noting that Locations A and D were adjacent to academic buildings comprised of lecture halls and that the end of baseline commenced around the time of finals week (which results in less foot traffic in academic buildings and may explain the decrease in cigarette butts). Location A featured an average of 68.67 (range = 57-77) cigarette butts collected in the pre-policy baseline that reduced to an average of 6.25 (range = 1-17) after the policy implementation. Location B featured an average of 70.33 (range = 62-76) butts collected in baseline that reduced to 7.63 (range = 2-20) following the policy implementation. Location C featured an average of 375.3 (range = 283-471) butts collected in baseline that reduced to 83 (range = 36-141) following the policy implementation. Location D featured an average of 119.3 (range = 71-174) butts collected in baseline that reduced to 3 (range = 0-7) following the policy implementation.

Figure 3 displays post-policy cigarette butt counts at each location as a percentage of baseline. Each data point in the scatter dot plot comes from the cigarette-butts-collected count from Figure 1, but standardized against that location's average baseline count to yield a percentage reduction from baseline. The horizontal lines depict average percentage reduction; error bars represent the 95% confidence interval. Notably, percentage reduction confidence intervals do not contain the value 0 in any location; accordingly, we can infer a significant decrease from baseline for all locations.

The results of GLS regressions suggested both Model III (4 parameters) and Model IV (2 parameters) performed well. Results of an LRT indicated that Model IV provided a more parsimonious description of the observed data, χ^2 (2) = 1.08, p = .58. Model II was fitted to justify the added complexity of the AR1 correlation structure in Model IV. The results of a Durbin-Watson test indicated the presence of significant, positive correlation and a violation of independent errors in Model II (value = 0.94; $p < .001$). Furthermore, the introduction of random effects to Model IV did not significantly improve the performance of the model, χ^2 (1) = 1.94, p = .16. As such, we review only the estimates emerging from Model IV using GLS. Results indicated a baseline rate of 159.95 cigarette butts collected across all sites, and the introduction of the policy resulted in a significant decrease in these rates (b = -124.97, T = -4.58, $p < .0001$). The rates observed across sites and observations decreased from an average level of 159.95 in baseline to 34.99 following policy enactment, a decrease of 78%.

Discussion

This study provides a behavior analytic contribution to the growing literature on campus tobacco policies in the United States. The policy development process to which this study contributed represents a successful integration of behavioral science, reminiscent of proposed behavioral contributions to policy efforts (e.g., Fawcett et al., 1988). Planning began by securing social validity of the proposed policy via broad surveys. Stakeholder teams used data to make an informed decision in the policy language, implementation approaches, and communication. The steering committee used behavioral insights from crowdsourced data collection to pinpoint areas for baseline investigation (e.g., the heatmaps to inform data collection sites) and potential messaging interventions (e.g., signage regarding the policy on doors of buildings near those sites). From the start, behavior analysts had a say in shaping the process.

Upon implementing the campus-wide policy, we observed decreases in butt litter in all locations, with some exceptions. That the third baseline collections of Locations A and D reflect a decrease in butts and that those of Locations B and C reflect an increase was thought likely to be the result of the relative breakdown of student and faculty/staff contributions to litter accumulation. Specifically, students tend to traffic Locations A and D, while faculty/staff tend to traffic Locations B and C. Hypothetically, proximity to exam week and end-of-semester responsibilities may have a suppressive impact on student smoking (i.e., less "free-time"), whereas corresponding warmer weather may have an elevated effect on general smoking (insofar as non-students would be more likely to smoke due to pleasant outdoor temperatures without the imposition of end-of-semester coursework). This apparent effect is mirrored—albeit in a subdued fashion due to lower counts—on 4/26/19. A comprehensive examination is required to determine compliance across campus populations.

Even after several semesters of implementation, counts remained variable in Location C. The busy campus dining facility housed therein likely influenced the maintained elevated level of smoking refuse. Following policy implementation, we found much of the litter in this region in a small walled-off area obscured by low-hanging vegetation (a location where dining hall employees observedly took breaks). We note that the primary effects of the intervention could be limited to those students, staff, and employees directly affiliated with the university (i.e., those for whom contingencies are more direct) rather than contracted persons. Alternatively, and as a leading possible limitation of the current investigation, observed litter may be just a subset of that which exists on campus. Our search focused on public regions wherein smoking was previously observed with relative frequency. Still, ban enactment may have forced many of these smokers to less conspicuous locations outside of our targeted observation zones (as in the described "break area").

The methods and results of the present study embody an instance of tobacco-use policy evaluation independent of self-report. More specifically, the data suggest a relative success of the policy in eliminating cigarette smoking on a university campus, mimicking results previously reported by studies conducted in comparable locations (e.g., Lee et al., 2011; Pires et al., 2016; see also Bardus et al., 2020). Readers should consider several limitations in the interpretation of these results. The focus on solely tobacco litter provides less information on policy effects than a more direct observation approach (e.g., inability to extrapolate butt count to an approximate count of policy compliers, only with the outcome of non-compliance). Unfortunately, we could glean little evidence of the relative reallocation of behavior toward untracked nicotine substitutes (e.g., electronic cigarettes[2]), given they would not necessarily leave a permanent product. Resource constraints prevented the adaptation of observer reliability for use in field collection. We acknowledge the visual acuity fatigue that likely arose during extended collection periods as a factor hampering a possible weekly butt count; readers should interpret reported values within a relatively narrow but incalculable margin of error. Although combusted-butt counts are an imperfect approximation of site-specific smoking, count-based conclusions support independent substantiation of smoking-policy effects.

Amassing a body of knowledge on a best-practice interface for behavior analysis and community research (e.g., Fawcett, 2021) is an important, enduring cultural challenge. We hope the present study provides a brief exemplar to support the use of outcome measures and supplementary statistical analysis for deriving policy-supportive data. As a proxy for broader-

[2] We note, however, that shifting smoking away from combustible cigars/cigarettes and towards e-cigarettes could nevertheless be beneficial within a harm reduction standpoint (see Fairchild et al., 2014).

scale policy evaluation, the present study underscores the challenges associated with the application of rigorous standards of methodology. The necessary analytic sacrifices (e.g., time-staggering, observer reliability) accentuate the hurdles—methodological concerns in design, interpretation, and reception—overcome by past and future attempts to support policy development. Future research efforts should include longer spanning investigations targeting alternative, perhaps more behaviorally valid measures (e.g., direct observation of smoking), where resources permit.

Other approaches, such as extending examination to partner sites at staggered timing (i.e., multiple baseline design; MBD), may be appropriate and feasible in some situations (e.g., when at least two independent groups/communities exist where policy/treatment implementation could be staggered), but less practical in others (e.g., implementing a staggered tobacco ban on a single campus). Limitations notwithstanding, this cornerstone behavior analytic methodology has made its way into the public health literature with some optimism as an alternative to group randomized trials (GRT). Hussey and Hughes (2007), discussing the benefits of a MBD, note that "the intervention is never removed once it has been implemented…which may alleviate ethical and/or community concerns" (p. 183). Such designs are best-suited when interventions target individuals rather than groups, and when changes in the variable of interest are rapid and large (Rhoda et al., 2011).

Application of prototypical behavior analytic empirical standards to examining public policy may be limited only to exceptional circumstances. Field discourse highlighting behavior analytic in-roads to areas of social concern (e.g., public health; Normand et al., 2021) presents a potential need for venturing beyond the easy-to-frame behavioral deficit or excess. Focusing instead on replicable demonstrations of less-than-ideal environmental arrangements should prove pragmatically preferable and advantageous (Lutzker & Whitaker, 2005). Indeed, there is a rich history of behavior analysts using methods outside of typical single-case experimental designs to address complex policies when necessary. As some examples, (a) Wilde (1991) published a series of correlations between vehicular crashes and potential contextual influence, (b) Schnelle and Lee's (1974) use of an integrated moving-averages approach to analyzing an A-B comparison design to assess prison policy effects against baseline, (c) Seaver and Patterson's (1976) analysis of variance to examine effects of feedback on fuel consumption, and (d) Schroeder and colleagues' (2004) use of logistic regression to examine effects using newsletters to spur political action, to name a few.[3] Alternative single-case experimental designs may also produce more successful demonstrations of experimental control, where applicable (e.g., interrupted time-series; see Biglan et al., 2000; see also Bernal et al., 2017).

The described study represents an analysis of campus-level policy solely. Given the need for empirical evaluation of and data-driven support for policy enactment (see Biglan et al., 2020) to impact broader cultural change (see Baer et al., 1987; Fawcett et al., 1988), we believe such a pursuit is worth the initial analytic sacrifice (mainly when the alternative is *no data*; see also Critchfield & Reed, 2017). This work supports the use of a tobacco-free policy—on a campus-scale—to inhibit combustible tobacco-product litter and presumably curb the prerequisite smoking behavior. As communities continue to ramp up efforts to yield elevated public and environmental health outcomes, similar policy evaluations should prove invaluable as a foundation from which to construct and implement successful cultural change.

[3] We note that these referenced papers were all pubished in *Journal of Applied Behavior Analysis* (*JABA*), despite not conforming to traditional single-case experimental design (i.e., the "analytic" dimensions of applied behavior analysis according to Baer et al., 1968). These exemplars provide additional support to the notion that "applied behavior analysis" is a fuzzy concept (Critchfield & Reed, 2017). We posit that these studies—and many others like them—were considered behavior analytic by *JABA* reviewers on the grounds that they fulfilled *most*–but not all–of Baer and colleagues' proposed dimensions of the discipline.

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Figure 1

Heat Map of Smoking Observed by University Students and Staff

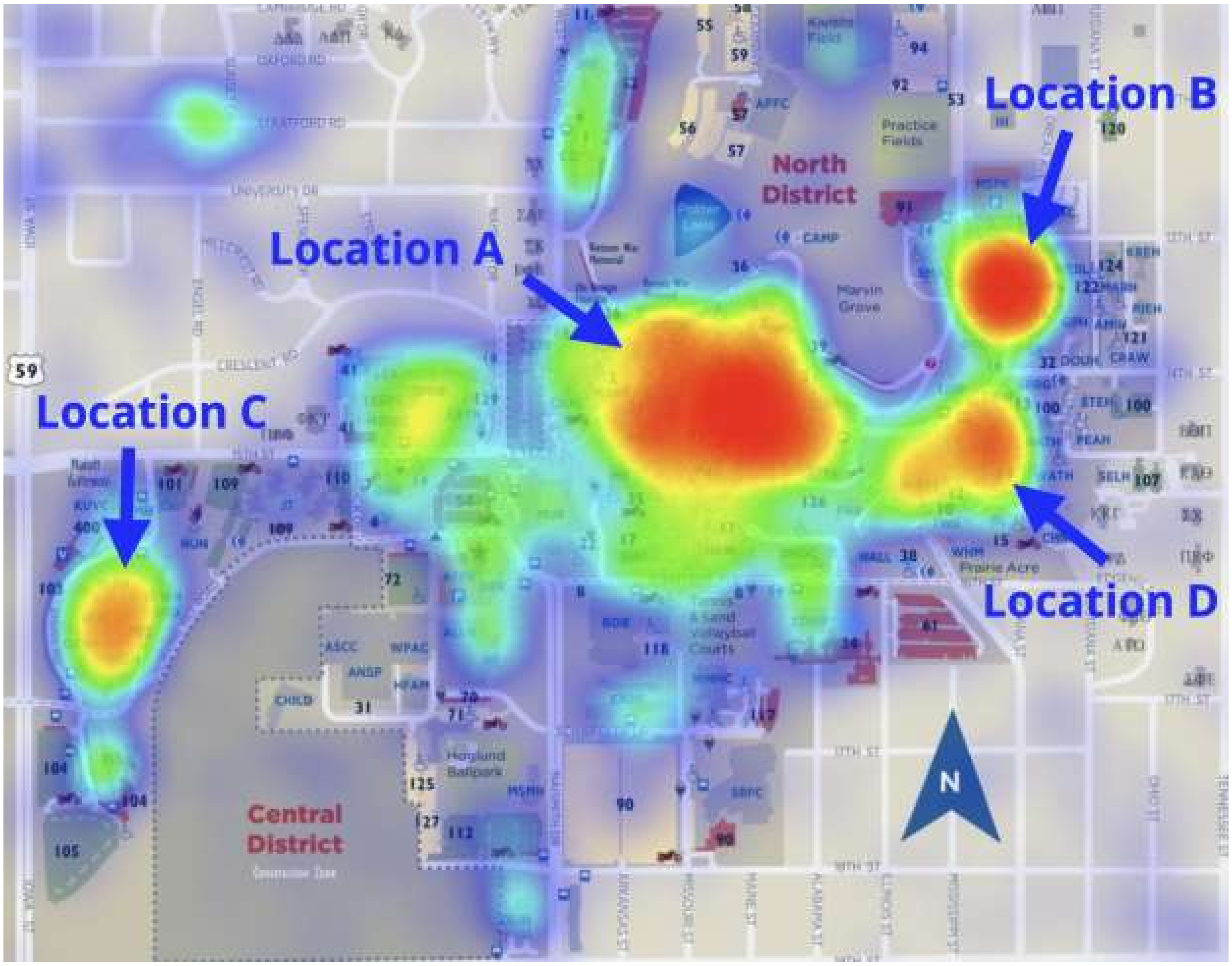


Figure 2

Combustible Tobacco Byproduct Collected at Identified Focus Sites

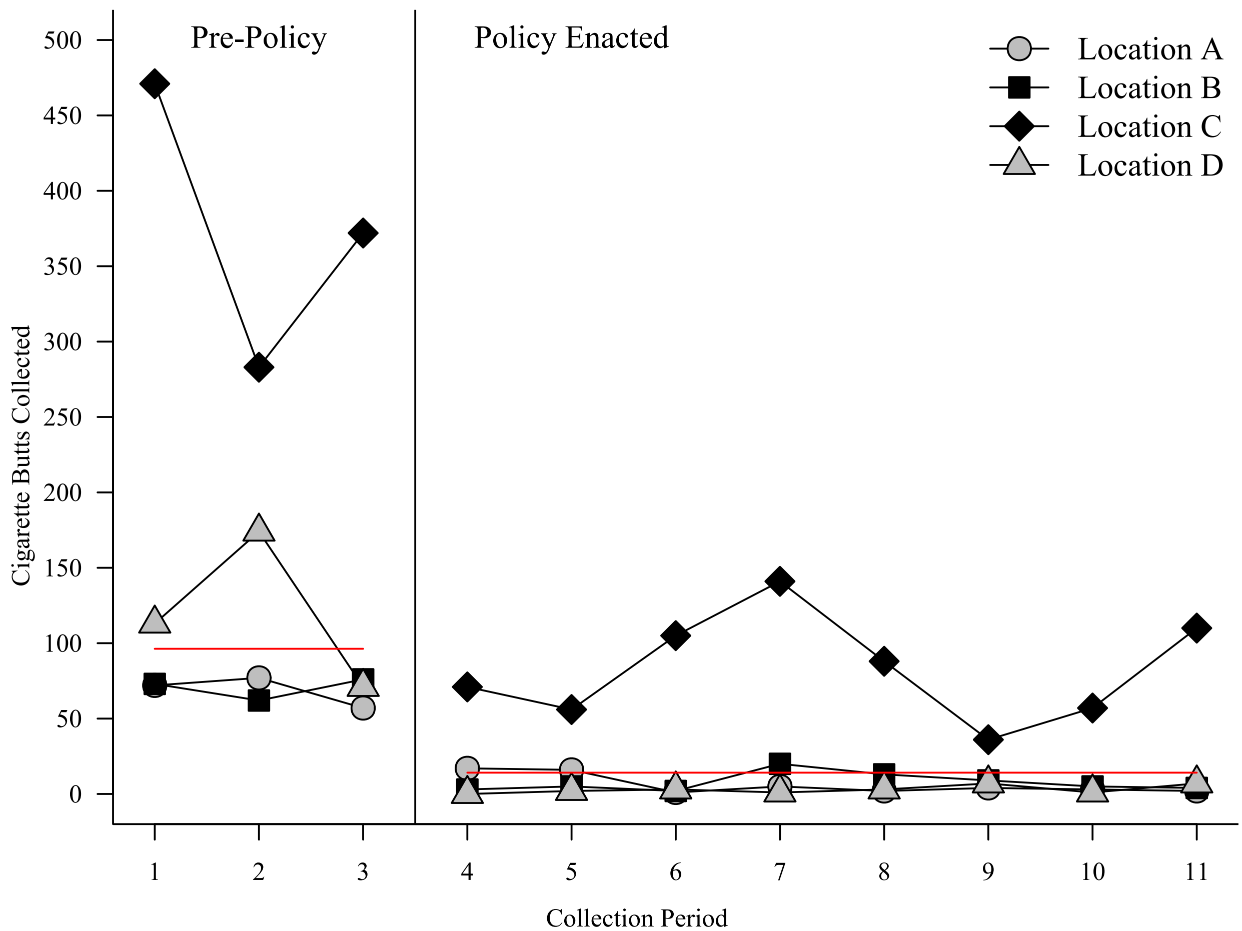
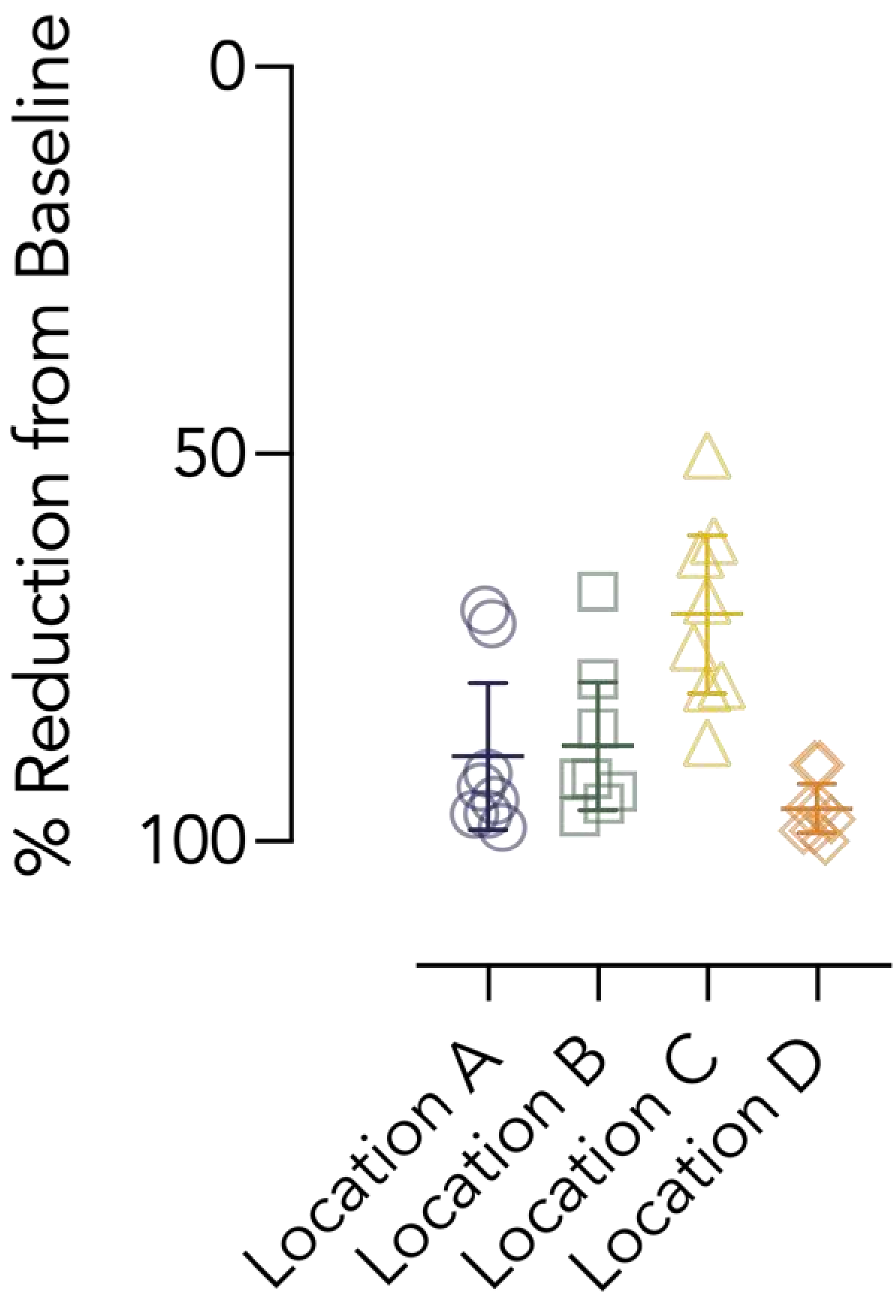


Figure 3

Reduction in Observed Byproduct as Percentage of Baseline Collection Following Policy Enactment



Note. Data are calculated based on baseline collection of least magnitude for each respective site. Error bars represent the mean with 95% CI.